Abstract

Breast cancer is a major global health concern and a leading cause of mortality among women. Early and accurate detection is crucial for effective treatment. Breast cancer is commonly diagnosed through imaging techniques such as mammography, ultrasound, thermography, and pathological biopsy. Each of these techniques has its own utility and limitations. Traditional diagnostic workflows heavily rely on radiologist expertise, which introduces variability and the potential for human error. To address these limitations, Computer-Aided Diagnosis (CAD) systems have emerged as valuable second-opinion tools, enhancing diagnostic accuracy and reducing reliance on manual interpretation. CAD systems integrate Artificial Intelligence (AI), Computer Vision, and Medical Image Processing (MIP) to improve diagnostic sensitivity and specificity, particularly during early-stage detection when intervention is most ef fective. Among AI techniques, Deep Learning (DL), especially Convolutional Neural Networks (CNNs) has shown exceptional performance in breast cancer detection by automatically extracting complex features from medical images, including mammograms, thermograms, ultrasounds, and histopathology slides. This thesis investigates the application of DL-based CAD systems for breast cancer diagnosis, with the goal of improving early detection, reducing diagnostic error, and supporting clinical decision-making. In this research advanced techniques such as attention mechanisms, optimization-driven feature selection, and boundary-aware enhancement methods has been explored. Emphasis is placed on enhancing the interpretability, robustness, and efficiency of DL models while maintaining high diagnostic accuracy. Ultimately, this thesis aims to develop lightweight, reliable, and clinically deployable DL models that can assist healthcare professionals in early breast cancer detection and expand access to advanced diagnostic tools across diverse clinical settings.